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Overreaction in Trading: Evidence from the intraday trading of SPDRs during the 2008 Financial Crisis

Justin D. Morscheck

Ph.D., School of Business Administration, Gonzaga University, Spokane, WA, United States of America

ORCID ID: 0000-0001-7613-5903

Abstract

Using intraday trading data during the 2008 financial crisis, from the Standard and Poor's Depository Receipt (SPDR) market, we test for evidence of the informational advantage of traders. In addition, we examine the effect of pricing error on trade price. If traders are rational, and have accurate information, they will only purchase an asset at a premium (discount) if they have reason to believe that the fundamental value of that asset will increase (decrease). Our results show that the trading price of the SPDR does not significantly predict the movement of underlying asset values. This finding is consistent with traders overreacting to disparities between price and underlying value during the financial crisis.

Keywords: *Overreaction; Intraday Stock Prices, Intraday Volatility, Stock Price Reversals, ETFs, Market Efficiency, Financial Crisis*

JEL classification*: G11, G14, G19*

Introduction

With the extreme volatility observed in financial markets during the 2008 financial crisis, considerable academic attention was paid to the impact that intraday traders had on the market. Were rational trading strategies behind the extreme volatility? Or were traders making decisions based on market-wide fear and overreactions to market swings? The broader concept of overreaction can be explained by the findings of Tversky and Kahneman (Kahneman & Tversky, 1974): people tend to make predictions based on short-term trends rather than a more rational probabilistic model. A probabilistic model is a prediction model based on past outcomes, with equal weighting of each outcome regardless of the sequence of occurrence. In this case, an individual will evaluate the frequency of past outcomes to make predictions about future outcomes. However, Tversky and Kahneman (Kahneman & Tversky, 1974) find that in the decision making process, individuals are over-valuing the impact of recent information and short-term trends, and undervaluing older information. This discovery in psychology can be applied to financial markets; suggesting that traders may overreact by over-valuing recent price trends and under-valuing less recent information. It has been shown that profitable trading strategies can be formed that take advantage of these overreactions by buying "out-of-favor" stocks (Fung, Mock, & Lam, Intraday price reversals for futures in the US and Hong Kong, 2000). Past research in this field has defined "out-of-favor" in a variety of ways. Such as, low price-earnings ratios, low book to market ratios, and relatively low past returns. Despite the variety of methodologies in each of these studies, they all share the same purpose of identifying investor sentiment and events of overreaction. An overreaction event occurs when the price of an investment is significantly different from the value of its underlying assets or fundamental value. Following this logic, when the price of an investment is significantly higher than its fundamental value, it suggests that traders are overly optimistic of its prospects. Conversely, when the price of an investment is significantly lower than its fundamental value, it suggests that traders are overly pessimistic. It is this key feature of divergence from fundamental value that creates the opportunity for an overreaction event. However, a major limitation in studying overreaction events is the lack of an objective method to identify fundamental value. There are few research settings where fundamental value is observable. However, one exceptional example is the case of the SPDR market. SPDRs provide an objective, and more importantly, a visible fundamental value. This creates an ideal setting for testing of market overreaction. In January 1993 the American Stock Exchange (AMEX) introduced Standard and Poor's Depositary Receipts (SPDRs). Of the various types of SPDRs, the most common is SPY. SPY, which trades like a traditional share of stock, is designed to track the performance of the S&P500 index. In addition to SPY, AMEX publishes an "Intraday Indicative Value," under the symbol SXV. Reported every fifteen seconds, SXV is calculated based on the last trading prices of the securities included in the S&P500 index. This represents the underlying trading value or fundamental value of the SPDR. It is because of this characteristic that SPDRs present the ideal dataset for testing overreaction and the efficiency of markets.

In an efficient market, the price of a security should reflect the value of its underlying assets. However, past research has shown significant disparities in the values of trade price and fundamental value (Glosten & Milgrom, 1985). The results of this study confirm this anomaly, as a share of SPY rarely trades at its fundamental value. While deviations from fundamental value create opportunities to earn significant profits, the results of this study suggest that traders are not successful in their attempts to take advantage of this mispricing. We find that the trading price of a SPDR has no significant predictive value of underlying fundamental value. We also document evidence of the "magnitude effect" found by De Bondt and Thaler (Thaler, De Bondt, & Werner, 1985). This effect refers to the action of extreme pricing errors that are followed by extreme reversals. Presence of the magnitude effect supports our theory of overreaction by traders.

Our paper proceeds as follows. Section 2 provides a discussion of past research in the field of overreaction. Section 3 is a description of the market for depositary receipts and the data used for the empirical investigation. Section 4 details the research methodology and results are presented in section 5. Lastly, section 6, provides a conclusion and interpretation of results

ETF Market and Literature Review

Exchange traded funds (ETFs) continue to be one of the fastest growing classes of financial products. They were introduced in 1993, and by the end of 2001, they held $79 billion in assets or 2.4 percent of the total assets held in equity mutual funds. The share of equity mutual fund assets held through ETFs doubled in 2000 and rose by nearly fifty percent in 2001. With several years of continued growth at this pace, the assets held in ETFs now rival the amount held in equity mutual funds. One of the most popular ETFs is the SPDR. Just ten years after they were created SPDRs became the most widely traded ETF in the world, having over $54 billion under management. More recently, that number has grown to over $78 billion. Figure 2 gives a visual representation of the evolution of trading volume over the last five years. Since 2002, the average daily volume has been over 10% of the total outstanding shares. The average annual growth rate was 46% over the last eleven years. In addition, the number of spiders has increased to a staggering 906,947,000 currently. The increase in trading volume combined with the increasing number of outstanding shares has resulted in SPDRs becoming one of the most actively traded securities on the AMEX. ETFs, like the SPDR, have soared to popularity because they offer traders many benefits, including relatively low trading costs, diversification, tax efficiency, and liquidity.

In perhaps the most influential work in the field of market overreaction, De Bondt and Thaler (Thaler, De Bondt, & Werner, 1985) sparked interest for future research with their confirmation of the overreaction hypothesis. This research was exciting in 1985 because the overreaction effect represented a behavioral principle that had not yet received widespread acceptance in the academic community. In their study "Does the Stock Market Overreact?" De Bondt and Thaler find that "loser" portfolios (constructed of stocks with relatively low past performance) outperform the market. Conversely, "winner" portfolios (constructed of stocks with relatively high past performance) underperform the market. De Bondt and Thaler then calculate a cumulative average return (CAR) for each portfolio. The difference in CAR between the "winner" portfolio and the "loser" portfolio is an astounding 24.6% (Thaler, De Bondt, & Werner, 1985). This finding that stocks that had underperformed in past periods, proceed to outperform in future periods, confirms the overreaction hypothesis. Since their initial investigation of overreaction, De Bondt and Thaler, along with other researchers, have continued to show that investors display a variety of behavioral biases (De Bondt, 1987).

In their 1998 study, Barberis, Shleifer and Vishny (hereafter, BSV) used findings from the field of psychology as inspiration for their model of investor sentiment; specifically, the concepts of conservatism and the representativeness heuristic (Shleifer, Barberis, & Vishny, 1998). Conservatism refers to the process by which a decision maker incorporates new information into their set of beliefs. More precisely, conservatism states that individuals incorporate new information slowly relative to a more rational, probabilistic decision-making model. The representativeness heuristic is descriptive of individuals overweighting the degree to which a sample represents the parent population when estimating the probability of an unexpected event (Kahneman & Tversky, 1974). For example, assume a basketball fan makes a three-point shot during the half-time entertainment of a basketball game. If onlookers conclude that because great basketball players make similar shots the fan will continue to make the basket, then they are demonstrating a representativeness heuristic. The danger in this behavioral bias is that it causes people to see patterns in completely random events.

Armed with these psychological phenomena, BSV created a crude model that only allows the market (one investor) to believe in one of two states of nature: (1) mean reversion, and (2) trending (Shleifer, Barberis, & Vishny, 1998). When the first state prevails, the investor is told that movements of price in one direction will be followed by a swing in the opposite direction. In the second state, the investor is told that prices will continue to trend in the direction they are moving. It is up to the investor to decide which state of nature prevails based on the action of prices. In a variation of this model, BSV changes the information the investor has regarding the pattern and frequency of each state. For example, in one testing approach they inform the investor that the states will alternate from one period to the next. In another testing approach, they inform the investor that the state of nature is completely random from one period to the next. In conclusion, BSV's empirical results suggest that investors are displaying both under and overreaction, analogous to findings of conservatism and representativeness heuristic in psychology studies.

In a similar model of investor sentiment, Hong and Stein (Hong & Stein, 1999) confirm the findings of market over and underreaction by BSV and shed light on the relationship between under and overreaction. In their study, instead of having one investor subject to two states of nature, Hong and Stein create a model that has two different investors, each bound to a specific investment rationale. Investors of type one are labeled "newswatchers." Newswatchers pay no attention to an asset's past prices. They make their investment forecasts based solely on new information about future fundamentals. Type two investors, labeled "momentum traders," are only allowed to make investment forecasts based on past prices.

Hong and Stein then inform the two types of investors that information will process gradually into the group of newswatchers. As newswatchers trade alongside momentum traders, an interesting relationship is revealed. The momentum traders, assuming price is increasing because of good news on future fundamentals purchase assets that are increasing. However, as it turns out, momentum traders that are "late to the party" observe price increases due to the earlier momentum trading. This causes an acceleration of prices to the point of overreaction when newswatchers begin to drive prices back towards fundamental value (Hong & Stein, 1999). Through this process it is observed that underreaction is causing future overreaction.

In a related study of market overreaction, Fung and Lam (Fung & Lam, Overreaction of index futures in Hong Kong, 2004) found that it is possible to create profitable trading strategies, even after accounting for transaction costs, risk adjustment and execution time-lag. In their study, Fung and Lam use data from the

Hang Sang Index Futures market in Hong Kong. Their model is based on identifying points within the trading day where the relative pricing error (RPE) is at extreme levels: either abnormally positive or negative. Their definition of relative pricing error is the difference between trade price and fundamental value divided by fundamental value. If the market overreacts, futures return from one period to the next after a large (small) pricing error should be negative (positive). Their null hypothesis states that for there to be a lack of significant pricing error in the futures market, the return after a relatively high or low pricing error will not be significantly different from zero (Fung & Lam, Overreaction of index futures in Hong Kong, 2004). After finding evidence of overreaction in this model, they test for the “magnitude effect” found by De Bondt and Thaler (Thaler, De Bondt, & Werner, 1985).

The “magnitude effect” in this context refers to extreme swings in relative pricing error and the corresponding reversion of price towards fundamental value. In other words, if there is an extreme pricing error (i.e., a significant premium), then a significant reversal should follow. To test for the presence of this effect, Fung and Lam regress the subsequent futures return on relative pricing error. The results found a negative regression slope which indicated that the “magnitude effect” is present. In conclusion of their study, they test the economic significance of a trading strategy based on exploiting the observed overreaction. The results were important to subsequent research in the field of overreaction. It is found that after all transaction costs were accounted for, they are still able to generate 0.069% daily profit, significant at the 5% confidence level. This results in an annualized return of 19%. In plain terms, this trading strategy profits by taking the opposite position of extreme relative pricing errors. In their own words, “the strategy buys when most people want to sell and sells when most people want to buy” (Fung & Lam, Overreaction of index futures in Hong Kong, 2004).

Data

Formed by a subsidiary of the AMEX, SPDRs were created to provide investors an investment option that would essentially allow them to invest directly in the S&P 500. The trust consists of substantially the same stocks and weighting as the S&P 500 and delivers similar returns. In addition to SPY, the AMEX publishes a value for SXV5. This symbol represents the last trade price of all securities listed in the S&P500 and is considered the “underlying trading value.” SPDRs are designed to approximate 1/10th of the value of the S&P500 index so that the price reflects that of a typical share of stock. SPDRs are organized as unit trusts. In order to maintain the integrity of the trust, the trustee routinely adjusts the portfolios in response to changes in the identity and weightings of securities within the index. A change in the identity or weighting of an index security will result in a corresponding adjustment to the SPDR portfolio the following day, assuming the NYSE is open for business that day. The value of a SPDR fluctuates in relation to changes in the value of the portfolio. However, the market price of a SPDR is not identical to the net asset value (NAV) or fundamental value (SXV) but, historically, these values have remained close.

The data set for this study includes tick by tick data for all trading days during the month of August 2008. Trades captured for this dataset occur between the normal trading hours of 9:30am to 4:00pm, EST. Additionally, only trades that occur within these times and on days when the markets are open for business are included. In addition to trade price (SPY) and underlying value (SXV), the data also include corresponding values for trade volume, and bid/ask prices. For stock symbol SPY there are 24,660 observations. Along with price, there are corresponding data for trade time (to the second), actual trade price per share (to the ten-thousands decimal), trading volume (actual number of shares traded), as well as identifying the exchange on which the trade is executed. For symbol SXV, there are 31,338 observations. Each observation has a value for trade time (to the second) and intraday indicative value (to the tenths decimal), which is calculated and reported every 15 seconds. Average trade price for the SPY over the sample period is $128.81, with a standard deviation of $2.48. SXV averaged $129.23, with a standard deviation of $2.27. The average bid/ask spread is 0.16% with a standard deviation of 0.071%.

Research and Methodology

The relative pricing error (RPE) is calculated by subtracting the fundamental value (SXV) from the corresponding trade price (SPY), and scaling by fundamental value.

$$RPE = \frac{SPYt - SXVt}{SXVt} \cdot 100 \qquad (1)$$

When RPE takes on a negative (positive) value it indicated that SPY is trading at a discount (premium), and when RPE equals zero, SPY is said to be trading at its fundamental value. In the dataset, average RPE is -0.23%, with a standard deviation of 0.68%, indicating that SPY traded on average 0.23% lower than its fundamental value. For our time period, SPDRs trade at a discount to fundamental value 72% of the time, compared to trading at a premium only 28% of the time, with a RPE of zero happening less than half a percent of the time.

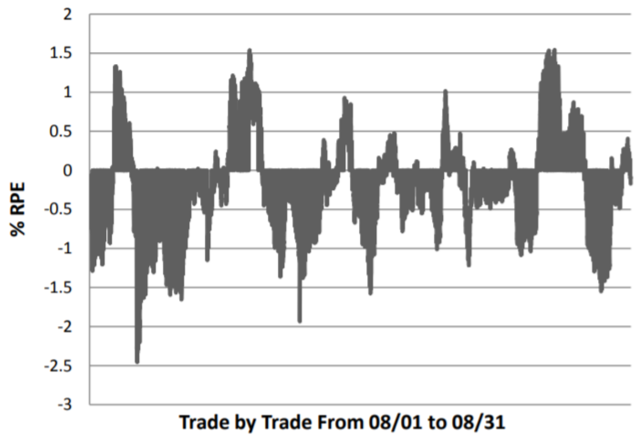

Figure 1: Relative Pricing Error for 31 days of August 2008

The research method used in this study is a combination of two prior works in the field of overreaction. The key principal of the methodology of this study is based on the model of Fung and Lam (Fung & Lam, Overreaction of index futures in Hong Kong, 2004). In their study, Fung and Lam use regression analysis to determine if the slope of futures price on relative pricing error is negative or positive. The sign of the slope either confirms or denies the presence of the magnitude effect[1]. For this study, it is the predictive value contained in the movement of trade price that is of interest. For example, if traders are acting on accurate information, an increase (decrease) in price would predict an increase (decrease) in fundamental value. Therefore, when fundamental value is regressed on trade price, the slope of the regression line should prove to be significantly greater than zero. In order to thoroughly test these hypotheses, techniques are also borrowed from Chan (Chan, 1992). Chan, looking to identify the lead-lag relationship between an index and its corresponding futures, partitioned the trading day into various intervals. This allowed for the identification of trends in the relationship over different time intervals. In order to test the accuracy of trader's information, each trading day is partitioned into thirty-second, one, five, ten, and thirty-minute return intervals. In each interval, the last observation for trade price (SPY) and underlying value (SXV) is identified. These price observations are used to calculate thirty-second, one, five, ten, and thirty-minute returns for both SPY and SXV. The return for SPY is calculated by dividing the trade price at t+1 by price at time t, then taking the natural log of the result. In recognition of the bid/ask effect[2] we also test an alternative proxy for price. The mid- point between bid and ask prices (MID) is used in place of SPY for an additional analysis. After all, one-

[1] *The greater the magnitude of pricing error, the greater the following reversal will be (Thaler, De Bondt, & Werner, 1985). An estimated slope that is significantly less than zero indicates presence of the magnitude effect.*
[2] *The bid/ask effect can obscure results due of the disparity between bid and ask price from one trade to the next.*

period returns have been calculated, the returns of SXV are regressed on same period returns of SPY, one-period lagged returns of SPY, and two- period lagged returns of SPY.

$$RX_t = \propto + \beta \cdot RP_t + \varepsilon_t \quad (2)$$
$$RX_t = \propto + \beta \cdot RP_{t-1} + \varepsilon_t \quad (3)$$
$$RX_t = \propto + \beta \cdot RP_{t-2} + \varepsilon_t \quad (4)$$

RXt represents the return of SXV at time t, and RPt represents the return of price at time t. In this model, if traders are rational, β should be significantly greater than zero. This would imply that traders are acting on accurate information, causing the return of price to positively affect return of fundamental value.

The second part of this study tests for the presence of the magnitude effect. This is accomplished by again partitioning trading days into thirty-second, one, five, ten, and thirty-minute intervals. The one-period returns calculated for SPY are then regressed on relative pricing error (RPE). RPE is calculated by subtracting fundamental value from trade price, dividing by fundamental value and multiplying by one hundred; as shown in equation (1). Returns of price (RPt) are regressed on $RPEt$, $RPEt$−1, and $RPEt$−2.

$$RPt = \propto + \beta \cdot RPEt + \varepsilon t \quad (5)$$
$$RPt = \propto + \beta \cdot RPEt{-1} + \varepsilon t \quad (6)$$
$$RPt = \propto + \beta \cdot RPEt{-2} + \varepsilon t \quad (7)$$

Presence of the magnitude effect would mean a value for β in equations (6) and (7) that is significantly less than zero. In plain terms, the more extreme the pricing error, the greater the following price reversal will be. For example, if SPY is trading at an extreme discount, the following period's return for SPY would be significantly positive.

Findings

Table 1 presents the results for the regression analysis of RX on RP for the 30- second interval. It is found (at all lag levels) that RP is not significantly predicting the movement of RX. For the thirty-second interval the average number of observations is 8,580.

Table 1: Regression results of RX on RP (30-second interval)		
RX represents return of fundamental value. RP represents return of trade price.		
Panel A. RXt on RPt		
Intercept, α (t-stat)	3.9E-06	(1.71)
Coefficient, β (t-stat)	0.00195	(0.52)
R-square	0	
n	8581	
Panel B. RXt on RPt-1		
Intercept, α (t-stat)	3.39E-06	(1.39)
Coefficient, β (t-stat)	0.000426	(0.11)
R-square	0	
n	8579	
Panel C. RXt on RPt-2		
Intercept, α (t-stat)	1.79E-06	(0.73)
Coefficient, β (t-stat)	0.00292	(0.72)
R-square	0.0001	
n	8577	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 2 presents the regression results for RX on RM, where RM is the return of the midpoint between bid and ask prices. This adjustment of the price variable has no significant impact on the results. There is still no evidence that price is significantly predictive of underlying value at any of the lag levels. The results indicate that for the thirty-second interval the null hypothesis of β = 0 cannot be rejected.

Table 2: Regression results of RX on RM (30-second interval)		
RX represents return of fundamental value. RM represents return of mid-point of bid and ask prices.		
Panel A. RXt on RMt		
Intercept, α (t-stat)	2.73E-06	(1.71)
Coefficient, β (t-stat)	0.00324	(0.79)
R-square	0	
n	15350	
Panel B. RXt on RMt-1		
Intercept, α (t-stat)	3.32E-06	(1.99)*
Coefficient, β (t-stat)	-0.00171	(-0.39)
R-square	0	
n	15349	
Panel C. RXt on RMt-2		
Intercept, α (t-stat)	3.14E-06	(1.86)
Coefficient, β (t-stat)	0.0033	(0.76)
R-square	0	
n	15350	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 3 presents the results of the one-minute interval regression of RX on RP. The results show that the slope of the regression line is not significantly different from zero. The t-statistic for the slope at 0, 1, and 2 period lag levels is 0.53, -0.21, -1.03 respectively. This indicates that movement of SPY has no significant predictive value of movement of SXV. And the null hypothesis of β = 0 cannot be rejected for the 1-minute interval at any lag level. It is also found for the one-minute interval that in the regression of RX on RM there is no statistical significance of slope.

Table 3: Regression results of RX on RP (1-minute interval)		
RX represents return of fundamental value. RP represents return of trade price.		
Panel A. RXt on RPt		
Intercept, α (t-stat)	6.06E-06	(1.61)
Coefficient, β (t-stat)	0.00307	(0.53)
R-square	0	
n	6707	
Panel B. RXt on RPt-1		
Intercept, α (t-stat)	6.66E-06	(1.72)
Coefficient, β (t-stat)	-0.00126	(-0.21)
R-square	0	
n	6706	
Panel C. RXt on RPt-2		
Intercept, α (t-stat)	6.6E-06	(1.68)
Coefficient, β (t-stat)	-0.00621	(-1.03)
R-square	0.0002	
n	6705	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 4 reports the results for the regression of RX on RP for the five-minute interval. No statistical significance of the slope is found in the regression lines of RXt on RPt or RXt on RPt-2. However, the slope for RXt on RPt-1 is found to be significantly less than zero at the 5% confidence level (t = -1.98). This indicates that the movement of SPYt is significantly predicting a movement of SXVt+1 in the opposite direction. In other words, if trade price increases (decreases) at time t then underlying value decreases (increases) at time t+1.

Table 4: Regression results of RX on RP (5-minute interval)		
RX represents return of fundamental value. RP represents return of trade price.		
Panel A. RXt on RPt		
Intercept, α (t-stat)	3.51E-05	(1.96)*
Coefficient, β (t-stat)	0.02711	(1.43)
R-square	0.0012	
n	1774	
Panel B. RXt on RPt-1		
Intercept, α (t-stat)	3.62E-05	(1.97)*
Coefficient, β (t-stat)	-0.03834	(-1.98)*
R-square	0.0022	
n	1773	
Panel C. RXt on RPt-2		
Intercept, α (t-stat)	3.22E-05	(1.76)
Coefficient, β (t-stat)	0.00412	(0.21)
R-square	0	
n	1772	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 5 reports very similar results for RX regressed on RM. When RXt is regressed on RMt and RMt-2, no statistical significance of slope is shown. However, as before, when RXt is regressed on RMt-1, a significant and negative slope is shown (t = -2.12). The null hypothesis of β = 0 can be rejected for RXt on RMt-1 and for RXt on RPt-1.

Table 5: Regression results of RX on RM (5-minute interval)		
RX represents return of fundamental value. RM represents return of mid-point of bid and ask prices.		
Panel A. RXt on RMt		
Intercept, α (t-stat)	3.49E-05	(1.95)
Coefficient, β (t-stat)	0.00934	(0.44)
R-square	0.0001	
n	1772	
Panel B. RXt on RMt-1		
Intercept, α (t-stat)	3.64E-05	(1.98)*
Coefficient, β (t-stat)	-0.04601	(-2.12)*
R-square	0.0025	
n	1771	
Panel C. RXt on RMt-2		
Intercept, α (t-stat)	3.23E-05	(1.76)
Coefficient, β (t-stat)	0.01039	(0.48)
R-square	0.0001	
n	1770	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Consistent with the one-minute and thirty-second intervals, Tables 6 and 7 show no statistical significance for the slopes of RX on RP and RM in the ten-minute interval. The negative slope coefficient that is observed in the five-minute interval period for RX on RPt-1 is not present in the ten-minute interval. For all lag levels the results show no evidence of RP or RM significantly predicting RX. The average number of observations for this interval is 890 and the average t-statistic of slope is -0.60. T null hypothesis of β = 0 cannot be rejected. Appendix B presents the regression results for RX on RP in the thirty-minute interval.

Table 6: Regression results of RX on RP (10-minute interval)		
RX represents return of fundamental value. RP represents return of trade price.		
Panel A. RXt on RPt		
Intercept, α (t-stat)	5.89E-05	(1.60)
Coefficient, β (t-stat)	-0.00788	(-0.26)
R-square	0.0001	
n	890	
Panel B. RXt on RPt-1		
Intercept, α (t-stat)	6.46E-05	(1.75)
Coefficient, β (t-stat)	-0.02362	(-0.78)
R-square	0.0007	
n	889	
Panel C. RXt on RPt-2		
Intercept, α (t-stat)	7.1E-05	(1.92)
Coefficient, β (t-stat)	-0.02327	(-0.77)
R-square	0.0007	
n	888	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 7: Regression results of RX on RM (10-minute interval)		
RX represents return of fundamental value. RM represents return of mid-point of bid and ask prices.		
Panel A. RXt on RMt		
Intercept, α (t-stat)	5.87E-05	(1.60)
Coefficient, β (t-stat)	-0.02728	(-0.83)
R-square	0.0008	
n	888	
Panel B. RXt on RMt-1		
Intercept, α (t-stat)	6.51E-05	(1.76)
Coefficient, β (t-stat)	-0.00597	(-0.18)
R-square	0	
n	887	
Panel C. RXt on RMt-2		
Intercept, α (t-stat)	7.39E-05	(2.00)*
Coefficient, β (t-stat)	-0.02847	(-0.86)
R-square	0.0008	
n	886	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

The results show no significance in the slope for lag levels of 0 and 2, with t- statistics of -0.58 and 1.84 respectively. However, the negative slope in the one-period lag that is observed in the five-minute interval is identified in this interval as well. In the regression of RXt on RPt-1, the estimated slope is -.115 at the 5% confidence level (t = -2.23). However, for RXt on RMt-1, the estimated slope is not significantly different from zero.

Table 8: Regression results of RP on RPE (30-second interval)		
RPE represents relative-pricing-error. RP represents return of trade price.		
Panel A. RPt on RPEt		
Intercept, α (t-stat)	1.22E-05	(1.77)
Coefficient, β (t-stat)	-3.3E-05	(3.53)
R-square	0.0014	
n	8586	
Panel B. RPt on RPEt-1		
Intercept, α (t-stat)	-4.3E-06	(-0.63)
Coefficient, β (t-stat)	-4E-05	(-4.35)**
R-square	0.0022	
n	8585	
Panel C. RPt on RPEt-2		
Intercept, α (t-stat)	8.43E-06	(1.05)
Coefficient, β (t-stat)	-2.1E-05	(-2.00)*
R-square	0.0006	
n	6402	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 8 reports the findings for the regression analysis of RP on RPE in the thirty- second interval. At both the one and two lag levels, the estimated slope coefficient is significantly less than zero[3]. In the regression of RPt on RPEt-1 the estimated slope is significantly negative, with a t-statistic of -4.35. The negative relationship between RP and RPE is also present in the two-period lag level, with a t-statistic of slope at -2.00[4]. Interestingly, the slope for the same period RP, regressed on same period RPE, is also significantly different from zero. However, the estimated slope in this case is greater than zero. The results show the null hypothesis of β = 0 can be rejected for all lag levels in the thirty-second interval.

Table 9: Regression results of RP on RPE (1-minute interval)

RPE represents relative-pricing-error. SPY represents return of trade price.

Panel A. RPt on RPEt		
Intercept, α (t-stat)	1.74E-05	(2.08)*
Coefficient, β (t-stat)	3.7E-05	(3.19)**
R-square	0.0015	
n	6708	
Panel B. RPt on RPEt-1		
Intercept, α (t-stat)	-2.39E-06	(-0.29)
Coefficient, β (t-stat)	-5.23E-05	(-4.52)**
R-square	0.003	
n	6708	
Panel C. RPt on RPEt-2		
Intercept, α (t-stat)	4.54E-08	(0.01)
Coefficient, β (t-stat)	-3.04E-05	(-2.47)*
R-square	0.001	
n	5997	

* Designates statistical significance at the 5% confidence level.

** Designates statistical significance at the 1% confidence level.

Table 9 presents the regression results for RP on RPE in the one-minute interval. Consistent with the thirty-second interval, the results show that the slope of the regression lines at all lag levels, are significantly different from zero; indicating the presence of the magnitude effect in the one-minute interval. Specifically, the estimated slope for RPt on RPEt is positive and significant at the 1% confidence level. The estimated slope for RPt on RPEt-1 is negative and significant at the 1% confidence level. Lastly, the estimated slope for RPt on RPEt-2 is negative and significant at the 5% confidence level. For all lag levels in the one-minute interval the null hypothesis of β = 0 can be rejected.

[3] *Significant at the 1% confidence level for one-period lag. Significant at the 5% confidence level for two- period lag.*
[4] *Significant at the 5% confidence level.*

Table 10: Regression results of RP on RPE (5-minute interval)		
RPE represents relative-pricing-error. RP represents return of trade price.		
Panel A. RPt on RPEt		
Intercept, α (t-stat)	2.38E-05	(1.90)
Coefficient, β (t-stat)	5.41E-05	(1.63)
R-square	0.0015	
n	1775	
Panel B. RPt on RPEt-1		
Intercept, α (t-stat)	-1.3E-06	(-0.05)
Coefficient, β (t-stat)	-0.00014	(-4.15)**
R-square	0.0096	
n	1775	
Panel C. RPt on RPEt-2		
Intercept, α (t-stat)	4.65E-06	(0.20)
Coefficient, β (t-stat)	-0.00011	(-3.35)**
R-square	0.0063	
n	1766	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 10 presents the results for RP on RPE in the five-minute interval. The estimated slope coefficient for RPt on RPEt is not shown to be significantly different from zero. However, consistent with the results in the thirty-second and one-minute intervals, both lagged values of RPE show significant and negative relationships with RP. This indicates presence of the magnitude effect in the five-minute interval as well. The estimated slope for RPt on RPEt-1 is negative and significant at the 1% confidence level with a t-statistic of -4.15. The slope for RPt on RPEt-2 is also negative and significant at the 1% confidence level.

Table 11: Regression results of RP on RPE (10-minute interval)		
RPE represents relative-pricing-error. SPY represents return of trade price.		
Panel A. RPt on RPEt		
Intercept, α (t-stat)	8.36E-05	(1.93)
Coefficient, β (t-stat)	7.52E-05	(1.23)
R-square	0.0017	
n	891	
Panel B. RPt on RPEt-1		
Intercept, α (t-stat)	6.14E-06	(0.14)
Coefficient, β (t-stat)	-0.000256	(-4.27)**
R-square	0.0201	
n	891	
Panel C. RPt on RPEt-2		
Intercept, α (t-stat)	1.34E-05	(0.31)
Coefficient, β (t-stat)	-0.000183	(-3.07)**
R-square	0.0106	
n	884	
* Designates statistical significance at the 5% confidence level.		
** Designates statistical significance at the 1% confidence level.		

Table 11 reports the regression results for RP on RPE in the ten-minute interval. As is the case in the five-minute interval, both lag levels of RPE show a negative and significant slope[5]. This confirms the presence of the magnitude effect in the ten-minute interval. The null hypothesis of $\beta = 0$ is rejected for RPt on RPEt-1 and RPt on RPEt-1. However, the estimated slope of RPt on RPEt is not significantly different from zero. Appendix D presents the results for the regression of RP on RPE in the thirty-minute interval. The results indicate presence of the magnitude effect in this interval as well. Both one-period and two-period lag levels show a negative and significant regression slope at the 1% confidence level. As is the case in both the five- and ten-minute intervals, the regression of RPt on RPEt is not significantly different from zero for the thirty-minute interval. In contrast, both RPt on RPEt-1 and RPt on RPEt-2 show slopes significantly less than zero; allowing for rejection of the null hypothesis.

Conclusion

The findings of this study show no significant relationship between the trade price of SPDRs and their fundamental value in intraday trading. Consistent with past research, this suggests that traders are making trades based on overreaction. The model assumes that an upward (downward) movement in trade price should predict a future upward (downward) movement in underlying value. In five different return intervals, the movement of trade price has no significant predictability of underlying value. The variation of using the mid-point of bid/ask spread instead of trade price has no effect on the statistical significance of the relationship. In both the five- and thirty-minute intervals, the results show a significant and negative slope in the regression of fundamental value on price[6]. This further supports the theory of overreaction. In these instances, the trade price is negatively affecting future fundamental value. For example, if traders are bidding up (down) the price at time period t, fundamental value at time t+1 goes down (up). This effect is like the overreaction found in the study of newswatchers and momentum traders, where momentum traders continue to bid up price based on previous momentum trading, rather than on accurate information of future fundamentals (Hong & Stein, 1999).

In addition to examining the relationship between trade price and fundamental value, this study also tests for the magnitude effect. The results show that the magnitude effect is indeed present across all time intervals. Similar to the findings of Fung and Lam (Fung & Lam, Overreaction of index futures in Hong Kong, 2004), the results show the greater the level of premium or discount, the greater the following reversal. This is consistent with the notion that traders are overreacting to extreme disparities between trade price and fundamental value. The results of this study are important to future research in overreaction for the following reasons. If traders are consistently trading in response to market noise and overreaction, they could significantly increase the daily volatility of the market. This volatility can lead to investor fear and a subsequent negative impact on the returns of several equity-based securities (Durand, Lim, & Zumwalt, 2007). However, if research in this field continues to document overreaction, and develop trading strategies that exploit this behavioral bias, then excess market volatility may be reduced. In addition to concerns of excess volatility, research in this field may also eventually contribute to a more holistic model for asset pricing, a model that incorporates variables representing observed human biases.

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[5] *Both one-period and two-period lags show slopes significantly less than zero at the 1% confidence level.*
[6] *See Panel B of Tables 7. & 8. And Panel B of Table 13.*

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Appendix

Appendix A: Regression results of RX on RM (1-minute interval)
RX represents return of fundamental value. RM represents return of mid-point of bid

Panel A. RXt on RMt		
Intercept, α (t-stat)	6.24E-06	(1.95)*
Coefficient, β (t-stat)	0.00238	(0.35)
R-square	0	
n	8446	
Panel B. RXt on RMt-1		
Intercept, α (t-stat)	6.4E-06	(1.93)
Coefficient, β (t-stat)	0.00221	(0.31)
R-square	0	
n	8445	
Panel C. RXt on RMt-2		
Intercept, α (t-stat)	7.47E-06	(2.23)*
Coefficient, β (t-stat)	0.000465	(0.06)
R-square	0	
n	8444	

* Designates statistical significance at the 5% confidence level.

** Designates statistical significance at the 1% confidence level.

Appendix B: Regression results of RX on RP (30-minute interval)
SXV represents return of fundamental value. SPY represents return
of trade price.

Panel A. RXt on RPt		
Intercept, α (t-stat)	0.000188	(1.83)
Coefficient, β (t-stat)	-0.03046	(-0.58)
R-square	0.0011	
n	306	
Panel B. RXt on RPt-1		
Intercept, α (t-stat)	0.0001917	(1.89)
Coefficient, β (t-stat)	-0.11539	(-2.23)*
R-square	0.0161	
n	305	
Panel C. RXt on RPt-2		
Intercept, α (t-stat)	0.0001416	(1.39)
Coefficient, β (t-stat)	0.0954	(1.84)
R-square	0.0111	
n	304	

* Designates statistical significance at the 5% confidence level.

** Designates statistical significance at the 1% confidence level.

Appendix C: Regression results of RX on RM (30-minute interval)
RX represents return of fundamental value. RM represents return of mid-point of b
and ask prices.

Panel A. RXt on RMt		
Intercept, α (t-stat)	0.0001894	(1.83)
Coefficient, β (t-stat)	-0.0208	(-0.38)
R-square	0.0005	
n	307	
Panel B. RXt on RMt-1		
Intercept, α (t-stat)	0.0001915	(1.87)*
Coefficient, β (t-stat)	-0.10254	(-1.91)
R-square	0.0119	
n	303	
Panel C. RXt on RMt-2		
Intercept, α (t-stat)	0.0001347	(1.31)
Coefficient, β (t-stat)	0.10499	(1.95)
R-square	0.0125	
n	302	

* Designates statistical significance at the 5% confidence level.

** Designates statistical significance at the 1% confidence level.

Appendix D: Regression results of RP on RPE (30-minute interval)
RPE represents relative-pricing-error. RP represents return of trade price.

Panel A. RPt on RPEt		
Intercept, α (t-stat)	0.0002537	(2.16)*
Coefficient, β (t-stat)	0.0002826	(1.71)
R-square	0.0096	
n	306	
Panel B. RPt on RPEt-1		
Intercept, α (t-stat)	6.185E-05	(0.53)
Coefficient, β (t-stat)	-0.000574	(-3.54)**
R-square	0.0395	
n	306	
Panel C. RPt on RPEt-2		
Intercept, α (t-stat)	4.824E-05	(0.42)
Coefficient, β (t-stat)	-0.000637	(-3.94)**
R-square	0.0487	
n	305	

* Designates statistical significance at the 5% confidence level.

** Designates statistical significance at the 1% confidence level.

Tic-by-Tic Data from 12:53pm to 12:54pm EST on 11/06/2008. SXV (underlying value) is shown in red. SPY (trade price) is shown in yellow. Trading volume is by yellow bars on x-axis.

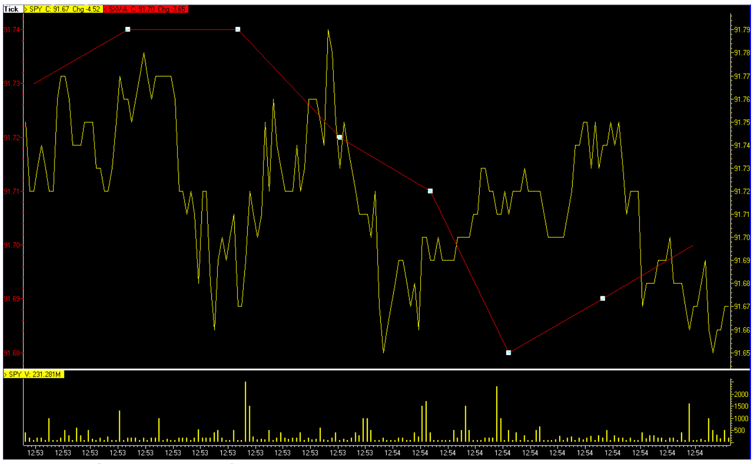

Figure 2: Snapshot of Bloomberg Terminal on 11-06-2008